Mapping seasonal impervious surface dynamics in Wuhan urban agglomeration, China from 2000 to 2016

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ABSTRACT

Numerous methods have been successfully applied to estimate the regional impervious surface dynamics based on spectral or spatial information from remote sensing imagery. However, previous methods mainly focused on mapping impervious surfaces at annual or decadal time scales. Few studies have attempted to map impervious surface dynamics at finer time scales, such as on a seasonal time scale using temporal information. This study aims to map regional impervious surface dynamics on a seasonal time scale by using time series Landsat data. The semi-supervised support vector machine (SVM) algorithm was employed for classifying impervious surfaces based on temporal characteristics, which were derived from seasonal time series biophysical composition index (BCI) and seasonal time series modified normalized difference impervious surface index (NDISI). The proposed method was validated over the Wuhan urban agglomeration (WUA) in China from 2000 to 2016. The results showed that impervious surfaces in the Wuhan urban agglomeration increased from 903.24 km² in 2000 to 3989.49 km² in 2016, with an annual growth rate of 20.10%. Additionally, the proposed method yielded reasonable average overall classification accuracy (up to 88%). Our results demonstrated that the proposed method could accurately map seasonal impervious surface dynamics based on temporal characteristics. This study could enable the monitoring of time-intensive impervious surfaces at a regional scale using remote sensing data.

1. Introduction

Impervious surfaces are mainly artificial structures such as pavement, building roofs, roads, sidewalks, driveways, parking lots, etc. Dramatic expansion of impervious surfaces is the result of the rapid urbanization process (Liu et al., 2013). Impervious surfaces, as one of the most important land cover type in urban areas, are a key indicator used to analyze the urbanization process and assess the environmental quality in cities (Arnold and Gibbons, 1996; Fan et al., 2015; Li et al., 2018). Numerous studies have examined changes in impervious surfaces and their impacts on the environment in the age of economic globalization. Satellite data has become one of the key data sources used to map regional impervious surfaces, such as DMSP/OLS nighttime light data (Liu et al., 2012; Ma et al., 2012; Zhang and Seto, 2011), Landsat archive (Ahmed and Ahmed, 2012; Bagan and Yamagata, 2012; Bhatta, 2009), MODIS imagery (Mertes et al., 2015), and multi-sensor imagery (Pandey et al., 2013; Shao and Liu, 2014; Zhang et al., 2012; Zhang et al., 2014).

Landsat data provides spatially consistent data at a fine spatial resolution and with a temporal frequency suitable for evaluating long-term regional impervious surface dynamics. Time series Landsat imagery has been successfully applied to characterize the dynamics of impervious surfaces. Zhang et al. (2013) applied time series classification to monitor impervious surface dynamics in the Zhoushan Islands from 1986 to 2011 (Zhang et al., 2013). Zhang and Weng (2016) monitored the annual dynamics of impervious surfaces in the Pearl River Delta, China, from 1988 to 2013, using time series Landsat imagery (Zhang and Weng, 2016). Gao et al. (2012) used the decision tree model to map the continuous expansion of impervious surfaces in the lower Yangtze River Delta region with time series Landsat imagery (Gao et al., 2012). Song et al. (2016) proposed a post-classification method to derive the magnitude, timing and duration of impervious surface changes from Landsat data in the Washington DC-Baltimore metropolitan region at an annual resolution from 1984 to 2010 (Song et al., 2016). Powell et al. (2008) demonstrated the value of a 35-year Landsat archive for monitoring impervious surface trends in areas undergoing rapid urbanization (Powell et al., 2008). Li et al. (2016) analyzed the spatial patterns of impervious surface distribution and its dynamic changes in various directions using Landsat imagery in the Hangzhou metropolis (Li et al., 2016). Previous methods typically

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focused on studying the annual or decadal changes in impervious surfaces. However, changes in impervious surfaces have no fixed date, because impervious surfaces were associated with human activities and urban construction. As a result, changes in impervious surfaces may occur within one year or less. This is especially true for rapidly urbanized areas. Thus, mapping impervious surface dynamics on a finer time scale is required.

In addition, previous studies typically differentiated impervious surfaces from other land cover types based on the spectral and spatial characteristics of land covers. However, for regional level impervious surface estimation, using only spectral and spatial characteristics was considered ineffective due to the limited spectral and spatial resolutions of Landsat data (Li et al., 2013; Weng and Hu, 2008; Zhang and Weng, 2016). Researchers have increasingly explored the potential of land cover temporal characteristics for mapping impervious surface dynamics using time series Landsat data. Zhang and Weng (2016) mapped annual pixel-based impervious surface dynamics based on temporal spectral differences, and the proposed method performed well when applied to the Pearl River Delta in southern China between 1988 and 2013 (Zhang and Weng, 2016). This study reduced the impact of the limited spatial resolution of Landsat images and spectral confusion of land covers. However, this study still monitored impervious surfaces at an annual time scale. Zhang et al. (2017) mapped impervious surface dynamics on a monthly time scale by fusing Landsat and MODIS time series in the Pearl River Delta, China from 2000 to 2015, and the results showed that distinguishability of land covers with similar spectral characteristics was enhanced because of the temporal information (Zhang et al., 2017). However, this study required additional data (MODIS data) for the generation of monthly time series data. Recently, few studies have introduced temporal characteristics of land covers to identify seasonal impervious surfaces. Schneider (2012) revealed the need to consider seasonality when attempting to identify urban change (Schneider, 2012). Therefore, in this study, the intent was to use the temporal characteristics of land covers to map impervious surface dynamics at a seasonal time scale.

The aim of this study was to develop a new methodology to map impervious surface dynamics on a seasonal basis using temporal characteristics from time series Landsat data. The procedures of the proposed method were as follows: (1) to generate a seasonal time series biophysical composition index (BCI) (Deng and Wu, 2012) and a seasonal time series normalized difference impervious surface index (NDISI) (Xu, 2010); (2) to develop an improved partial least squares regression (IPLSR) for extracting the temporal characteristics of impervious surfaces, pervious surfaces, and water from seasonal time series BCI and NDISI; (3) to classify temporal characteristics using semi-supervised support vector machine (SVM); (4) to develop seasonal scale temporal filtering to check the classification consistency and correct unreasonable land cover changes; and (5) to map the dynamics of impervious surfaces at a seasonal frequency in the Wuhan urban agglomeration of China from 2000 to 2016.

2. Methodology

To map the seasonal dynamics of impervious surfaces, original, unevenly sampled time series BCI and NDISI were first reconstructed as seasonal time series BCI and NDISI. Then IPLSR was proposed to derive the temporal characteristics from reconstructed time series BCI and NDISI. Next, the semi-supervised SVM algorithm was implemented to map seasonal impervious surfaces based on temporal characteristics. Finally, seasonal scale temporal filtering was proposed to improve the classification accuracies. The experiments were performed using MATLAB (MATLAB R2013a, MathWorks Inc. Natick, MA). The procedures for mapping the seasonal dynamics of impervious surfaces are as follows (Fig. 1).

2.1. Study area and datasets

The Wuhan urban agglomeration (WUA) is in the eastern part of Hubei Province (upper left longitude 112°30′E and latitude 29°05′N, lower right longitude 116°10′E and latitude 31°50′N) (He et al., 2017; Lu et al., 2014). The WUA centers on Wuhan within a radius of 100 km and includes the cities of Wuhan, Huangshi, Ezhou, Huanggang, Xiangning, Xiaogan, Xiantao, Tianmen, and Qianjiang. The WUA covers an area of 58,000 square kilometers, which is less than one third the size of Hubei Province (Tan et al., 2014). However, the WUA accounts for more than 50% of the population and GDP of the Hubei Province (Zeng et al., 2016). It has a humid subtropical climate with abundant rainfall. The average temperature ranges from 15 °C to 20 °C, and the mean annual precipitation is approximately 1300 mm (Zhang, 2017). The main reason for selecting the WUA as the suitable study area is because the area has experienced dramatic urban expansion in the past two decades. Since the theme of Wuhan (center of the WUA) is “Wuhan, Different Every Day”, the WUA is very representative of urbanization.

In this study, 150 Landsat surface reflectance climate data record (Landsat CDR) images were ordered and downloaded from the United States Geological Survey (USGS) Earth Explorer (reference system: WRS-2, path: 123, row: 39) for Landsat TM, ETM +, and OLI data. The day of the year (DOY) distribution of the collected Landsat data is shown in Fig. 2. Land cloud covers in the downloaded images were less than 10% of the data. Image subsets including Wuhan, Xiantao, Xiaogan, Xianning, and Tianmen were used to monitor impervious surface dynamics in the WUA area. The subsets covered an area of 23,426 square kilometers. The geographic location of the study area is shown in Fig. 3 with a true color composite image using Landsat TM 5 (October 31, 2000) bands 3, 2, and 1.

All the Landsat data were registered to the 1984 World Geodetic System Universal Transverse Mercator (WGS-84 UTM) Zone 49 North projection system and resampled at 30-m spatial resolution. Landsat 4–5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM +) surface reflectance data were generated from the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al., 2006), which applied MODIS atmospheric correction routines to Landsat L1 data products. Landsat 8 surface reflectance data were generated from the L2SR algorithm and were downloaded from the USGS products web portal (https://landsat.usgs.gov/provisional-landsat-8-surface-reflectance-data-available). Cloud, cloud shadow, and snow mask were calculated using the Fmask algorithm for all scenes (Zhu and Woodcock, 2012). The scan-line corrector (SLC) of the Landsat 7 ETM + sensor failed in 2003, which resulted in approximately 22% of the pixels per scene not being scanned. The locations of SLC-off data were identified using band-specific gap mask files in each SLC-off data product.

2.2. Generation of seasonal time series BCI, NDISI

Seasonal time series BCI and NDISI contributed to the temporal resolution of original time series Landsat data and provided a regular time series for extracting temporal characteristics. BCI was used to differentiate urban biophysical compositions. It was effective in identifying the characteristics of impervious surfaces and vegetation, and distinguishing bare soil from impervious surfaces (Deng and Wu, 2012). BCI, which involves Tasseled Cap (TC) transformation and V-I-S triangle model, is given as follows:

\[
\text{BCI} = \frac{\text{TC}_1 + \text{TC}_3}{2} - \frac{\text{TC}_2}{2} + \frac{\text{TC}_2}{2}
\]

where TC_1 was high albedo, TC_3 was low albedo, and TC_2 was vegetation. Each derived TC component was then linearly normalized to a range of 0–1. That is, TC_1 (i = 1, 2, and 3) were three normalized TC components. For calculating BCI, water bodies were masked out before
NDISI was applied to map original impervious surfaces of the study area.

\[
\text{NDISI} = \frac{\text{TIR} - (\text{MNDWI} \times \text{NIR} + \text{MIR})}{3}
\]

where TIR represents the digit number in the thermal band, NIR represents the digit number in the near-infrared band, and MIR represents the digit number in the mid-infrared band. Surface reflectance values of NIR and MIR bands and brightness temperature of the TIR band were rescaled from 0 to 255 to produce 8-bit digit number values (Sun et al., 2017). For computing NDISI, TIR bands were Landsat TM band 6, ETM+ band 6, and Landsat OLI band 10. NIR bands were Landsat TM band 4, ETM+ band 4, and Landsat OLI band 5. MIR bands were Landsat TM band 5, ETM+ band 5 and OLI band 6. MNDWI represented modified normalized difference water index.

\[
\text{MNDWI} = \frac{\text{VIS}_\text{G} - \text{MIR}}{\text{VIS}_\text{G} + \text{MIR}}
\]

where VIS_G was the green visible band (VIS).

Since available Landsat images were unevenly distributed during the study period due to cloud contamination, evenly distributed seasonal time series BCI and time series NDISI were reconstructed to extract regular temporal information. Given original time series \(T = \{T_1, T_2, \ldots, T_t\}\), \(t\) was the total number of years, \(T = \{\text{BCI, NDISI}\}\). That is, \(T_k(1 \leq k \leq t)\) represented time series BCI and time series NDISI in the \(k\)th year. Images within each year would be clustered into four parts: spring (March–May), summer (June–August), autumn (September–November), and winter (December–February). The partition rule was according to the climate change in the WUA. That is, \(T_{i}^{\text{sp}}, T_{i}^{\text{su}}, T_{i}^{\text{au}},\) and \(T_{i}^{\text{wi}}\) were spectral values of each part, respectively. Each part was generated based on the principle of least cloud cover. Cloud free images were selected as base images in each part. If there was no available cloud free image, the image with the least cloud cover was selected. To address the problem of missing values in the selected images, the modified neighborhood similar pixel interpolator (NSPI) (Zhu et al., 2012a) was applied to remove thick clouds from the Landsat subsets, and the geostatistical neighborhood similar pixel interpolator (GNSPI) (Zhu et al., 2012b) was applied to fill gaps in Landsat ETM+ SLC-off images. Here, NSPI and GNSPI algorithms were written in an interactive data language (IDL, a product of ITT Visual Information Solutions). Thus, the temporal dimension of reconstructed seasonal time series was redefined as total year number multiplied by four (16 × 4 = 64).

2.3. Extraction of temporal characteristics using IPLSR

Partial least squares regression (PLSR) (Abdi and Williams, 2013) is a robust multivariate regression method, which can be used to describe the relationship between different land covers and their associated index values. PLSR was something of a cross between multiple linear regression and principal component analysis (Abdi, 2010), which has been successfully applied in various disciplines (Farifteh et al., 2007). A more detailed overview of the PLSR algorithm can be found in (Geladi and Kowalski, 1986). Based on PLSR, this study developed the function

\[
\text{Fig. 1. The procedures for mapping seasonal dynamics of impervious surfaces in the WUA area.}
\]

\[
\text{Fig. 2. The day of the year (DOY) distribution of the collected Landsat data.}
\]
of improved partial least squares regression (IPLSR) for extracting temporal characteristics based on the statistical characteristics of seasonal time series BCI and NDISI.

For the time series study, the independent variables were seven statistical values of time series BCI and NDISI including mean value, variance, minimum value, maximum value, standard deviation, skewness, and average growth rate. The dependent variables were land cover categories including impervious surfaces, pervious surfaces, and water. Impervious surfaces were assigned the value of 1, pervious surfaces were assigned the value of 2, and water was assigned the value of 3. Land cover class \( C(x, y) \) for pixel \( p(x, y) \) was defined by IPLSR based on the statistical characteristics of the BCI and NDISI time series. The function of IPLSR is as follows.

\[
C(x, y) = w_1(p_{B1} + a_2p_{B2} + \cdots + a_7p_{B7}) + w_2(p_{N1} + b_2p_{N2} + \cdots + b_7p_{N7})
\]

where \( a_1, a_2, \ldots, a_7 \) and \( b_1, b_2, \ldots, b_7 \) were regression coefficients; \( p_{B1}, p_{B2}, \ldots, p_{B7} \) were seven statistical characteristics of \( p(x, y) \) in the BCI time series; and \( p_{N1}, p_{N2}, \ldots, p_{N7} \) were seven statistical characteristics of \( p(x, y) \) in the NDISI time series, respectively. \( w_1 \) and \( w_2 \) were weights determined by entropy evaluation. Since weights helped to know which coefficients were most important, weights were introduced to ensure the accurate number of various coefficients toward the final class. The advantage of different weights was that coefficients with the highest weights on the factor would have the largest effect on the determination of class. Here, regression coefficients were determined using the selected training samples. The size of the training samples was 20\% of the pixels in the entire study area. Random sampling strategy, which is called the equal sample rate (ESR), was applied to select training samples. The size of the training samples was 20\% of the pixels in the entire study area.

Temporal characteristic \( T_{B}^{(x,y)} \) for pixel \( q(x, y) \) in the image on date \( T \) was defined as follows:

\[
T_{B}^{(x,y)} = [q_{B1}, q_{B2}, \ldots, q_{B7}, q_{N1}, q_{N2}, \ldots, q_{N7}]
\]

where \( T_1 \) was the first image in the time series; that is, \( T_1 \) represented the spring image \( T_7 \). \( T_r \) was the image in the \( r \)-th year, \( 1 \leq r \leq 16 \). Temporal characteristics were next used for semi-supervised SVM.

2.4 Classification based on semi-supervised SVM

SVM has been successfully employed in the classification field due to its good generalization ability with limited training samples and globally optimal performance with high dimensions (Burges, 1998). To address the problem of classification with limited labeled data and large amounts of unlabeled data, a semi-supervised method for classification is proposed in this study. Semi-supervised SVM can incorporate prior information about samples into the SVM algorithm to improve the classification performance.

The procedure for the semi-supervised SVM algorithm is shown as follows.

1. Let \( X = [X_{\text{labeled}}^m, X_{\text{unlabeled}}^n] \) represented the dataset of temporal characteristics derived from IPLSR. \( l \) represented labeled training samples, and \( u \) represented unlabeled training samples. \( m \) and \( n \) were length and width of the study area, \( d \) was dimensions of the temporal characteristics for each pixel.
2. SVM was conducted to train labeled samples \( X_l \) to obtain classifiers \( C_1 \) using a polynomial kernel. Parameters of polynomial kernel were determined with a grid search method using a cross validation approach.
3. SVM was conducted to train labeled samples \( X_l \) to obtain classifier \( C_2 \) using a radial basis function. Parameters of radial basis function were also determined with a grid search method using a cross validation approach.
4. \( X^u \) was forecasted by classifier \( C_1 \) and pixels with high creditability were selected as forecasting result \( R_1 \). In the meantime, \( X^u \) was forecasted by classifier \( C_2 \) and pixels with high creditability were selected as forecasting result \( R_2 \).
5. The forecasting results \( R_1 \) and \( R_2 \) were compared, and pixels with the same label were put into \( X^l \). \( X^l \) was expanded and retrained to obtain new classifiers \( C_{1'} \) and \( C_{2'} \) using polynomial kernel and radial basis function respectively. Expanding \( X^l \) to retrain labeled samples could avoid the heavy manual labor for samples labeling, and updating the labeled samples dynamically could enhance the adaptive capacity of the proposed algorithm.
6. Finally, if all unlabeled training samples \( X^u \) were classified, exit loop. Forecasting results derived by \( C_{1'} \) and \( C_{2'} \) were compared to select the classifier with better performance as the final classifier.

In this study, labeled training samples were selected based on the similarity of temporal characteristics. Primary training samples were labeled by visual interpretation using Google Earth images. Then, labeled training samples were extended using the following rule.

\[
\min_{x \in X^u} d(x_i, x_i) < \alpha
\]

where \( x_i \in X^u \) was the labeled sample and \( x_i \in X^u \) was the unlabeled sample in adjacent region. \( d \) was the similarity distance between temporal characteristics of \( x_i \) and \( x_i \). \( \alpha \) was the threshold value. If
d(x₀, xₐ) < α, xₐ was labeled as the same class with x₀. Here, dynamic time warping (DTW) (Jeong et al., 2011) was applied to find an optimal match between two temporal characteristics. DTW distance provided the priori knowledge for noise estimation, which was helpful for comparing the differences between two temporal characteristics. The pseudo code for calculating DTW distance between two temporal characteristics can be found in Petitjean et al. (2011).

### 2.5. Seasonal scale temporal filtering

Temporal filtering has been successfully applied to check the consistency of time series classifications (Zhang and Weng, 2016). In this study, it is assumed that urbanization is an irreversible process, and a seasonal scale temporal filtering was developed to correct unreasonable land cover changes. This study defined the rule of unreasonable land cover changes within a 3 × 3 temporal window, which is shown in Table 1. Y represented reasonable land cover changes, and N represented unreasonable land cover changes. The procedure for the seasonal scale temporal filtering is shown in Fig. 4.

Here, a 3 × 3 temporal window was helpful to check the classification consistency both temporally and spatially (Zhang et al., 2017). For each image, the pixel was defined as certain pixel or uncertain pixel based on the classes in its 3 × 3 neighborhood. If the class of the pixel conflicted with half of the classes in its 3 × 3 neighborhood, this pixel was defined as an uncertain pixel. Then, the classes of uncertain pixels were determined by temporal filtering. For seasonal classification maps M={M₁, M₂, ..., M_T}, T was the number of classification maps. Before temporal filtering, seasonal time series segmentation was applied to segment original classification maps into Y parts. Y was the number of years during study period. Each part included four classification maps, which represented impervious surfaces distribution during the four seasons. That is, T = Y × 4. Then, the first image in each part made up a new time series {M₁', ..., M₃', ..., M₄'}. A 3 × 3 temporal window was conducted to check the classification consistency of the new time series. Unreasonable land cover changes were marked and corrected to improve the classification accuracies.

### 3. Results

#### 3.1. Seasonal time series BCI and NDISI

To evaluate the performance of time series reconstruction, Jeffries–Matusita (JM) distance (Dabboor et al., 2014) was applied to test the class separability of the original time series and reconstructed time series. The values of JM distance ranged from 0 to 2, and the class separability increased when the value approached 2. For each class, 100 test samples were randomly selected to calculate mean JM distances between impervious and pervious surfaces. Table 2 shows the JM distances using original time series and reconstructed time series. Table 2 demonstrates that the reconstructed time series can improve the class separability using the combination of BCI and NDISI. However, the JM distance between impervious surfaces and pervious surfaces (soil) was less than the JM distance between impervious surfaces and pervious surfaces (vegetation). Since JM distance measured the class separability among different land cover types in spectral domain, Table 2 shows that the problem of spectral confusion between impervious surfaces and soil still exists.

Impervious surfaces were divided into bright impervious surfaces and dark impervious surfaces, and pervious surfaces were divided into soil and vegetation. The land cover temporal profiles derived from

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**Table 1**

The rule of unreasonable land cover changes.

<table>
<thead>
<tr>
<th>Date M₋₁</th>
<th>Date M₀</th>
<th>Date M₊₁</th>
<th>Definition</th>
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<tbody>
<tr>
<td>Dense building area; Scattered building area</td>
<td>Vegetation; Soil; Water bodies</td>
<td>Dense building area; Scattered building area</td>
<td>N</td>
</tr>
<tr>
<td>Dense building area; Scattered building area</td>
<td>Dense building area; Scattered building area</td>
<td>Y</td>
<td></td>
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<tr>
<td>Vegetation; Soil; Water bodies</td>
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<td>Vegetation; Soil; Water bodies</td>
<td>Dense building area; Scattered building area</td>
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<td>Dense building area; Scattered building area</td>
<td>Dense building area; Scattered building area</td>
<td>Y</td>
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<td>Vegetation; Soil; Water bodies</td>
<td>N</td>
<td></td>
</tr>
</tbody>
</table>

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**Fig. 4.** The procedure for the seasonal scale temporal filtering.
seasonal time series BCI are shown in Fig. 5. The land cover temporal profiles derived from seasonal time series NDISI are shown in Fig. 6.

As shown in Figs. 5 and 6, different land covers had distinct temporal profiles. In time series BCI, bright impervious surfaces and dark impervious surfaces had positive values, and bright impervious surfaces had the highest values. Values of soil were approximately 0, and vegetation had negative values. In time series NDISI, bright impervious surfaces and dark impervious surfaces had positive values, and other land covers had negative values. Water bodies had the lowest negative values.

### 3.2. Temporal distances of temporal characteristics

To evaluate the effectiveness of temporal characteristics derived from IPLSR, DTW distance was used to measure temporal distances between the two land cover temporal characteristics. 200 impervious surface pixels (bright impervious surfaces and dark impervious surfaces), 200 pervious surface pixels (soil and vegetation) and 200 water

<table>
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<th></th>
<th>Original time series</th>
<th>Reconstructed time series</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCI</td>
<td>NDISI</td>
</tr>
<tr>
<td>Impervious surfaces-Pervious surfaces (vegetation)</td>
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<td>1.86</td>
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<tr>
<td>Impervious surfaces-Pervious surfaces (soil)</td>
<td>1.84</td>
<td>1.85</td>
</tr>
<tr>
<td>Impervious surfaces-Water</td>
<td>1.9</td>
<td>1.89</td>
</tr>
</tbody>
</table>

**Fig. 5.** The land cover temporal profiles derived from seasonal time series BCI.

**Fig. 6.** The land cover temporal profiles derived from seasonal time series NDISI.
body pixels were selected to calculate the mean DTW distances between each class (Table 3).

In Table 3, BI represented bright impervious surfaces, DI was dark impervious surfaces, PS was pervious surfaces (soil), PV was pervious surfaces (vegetation), and WB was water bodies. DTW distances ranged from 0 to 1. The DTW distance was asymptotic to 1 when temporal profiles were completely different and tended toward 0 when temporal profiles were identical. The within-class distances of BI-BI, DI-DI, DI-PS, PV-PV, and WB-WB were less than 0.5, and WB-WB had the lowest distance. The between-class distances of BI-PS, BI-PV, BI-WB, DI-PS, DI-PV, and DI-WB were above 0.7. The between-class distances of PS-PV, PS-WB, and PV-WB were above 0.8. Generally, water bodies were easy to differentiate from other land covers. In spectral domain, bright impervious surfaces were prone to confuse with bare soils, and dark impervious surfaces were easily confused with water bodies (Lu and Weng, 2006). As shown in Table 3, the between-class distance of BI-PS was higher than between-class distance of DI-PS, the between-class distance of DI-WB was similar as between-class distance of BI-WB, and the between-class distance of BI-PS was approximated to between-class distance of DI-PS. That is, the distances between impervious surfaces and pervious surfaces were enhanced in temporal domain. That is, temporal information can be used to alleviate the problem of spectral confusion.

### 3.3. Seasonal impervious surface dynamics

Fig. 7 shows the annual impervious surface maps in the study area from 2000 to 2016. The impervious surface images in the spring of each year were selected in Fig. 7. Impervious surface pixels, which include bright impervious surface pixels and dark impervious surface pixels, were displayed as the red area, pervious surfaces were displayed as the green area, and water bodies were displayed as the blue area.

Fig. 8 shows the quantification of impervious surface areas in the study area from 2000 to 2016. The following conclusions could be obtained:

(1) From 2000 to 2002 in the study area, urban areas grew slowly with an annual average growth rate of 3.69%. Impervious surfaces increased from 903.24 km² in 2000 to 1003.30 km² in 2002. Impervious surfaces in rural areas were scattered and showed no significant changes.

(2) From 2003 to 2006, the first rapid urban growth occurred in the study area with an annual average growth rate of 12.80%. Impervious surfaces increased from 1237.66 km² in 2003 to 1871.47 km² in 2006. Since 2003, the study area was in a fast urbanization stage due to the “Rise of Central China” strategy. Impervious surfaces expanded along the Changjiang and Hanjiang Rivers during this period.

(3) From 2007 to 2011, the study area underwent another accelerated urban sprawl with an annual average growth rate of 13.62%. Impervious surfaces increased from 1990.37 km² in 2007 to 3345.72 km² in 2011. During this period, the urban fringe district was the main area of city expansion and urban areas were clustered. The driving forces for urban growth during this period mainly included two parts: ‘Wuhan city circle’ was built in 2007 and Wuhan was defined as the core city in the central regions of China in 2010.

(4) From 2012 to 2016, the annual average growth rate dropped to 2.98%. Urban areas increased from 3471.75 km² in 2012 to 3989.49 km² in 2016. Most of the urban expansion occurred around the urban core area. In 2012, the study area entered the stage of stable urbanization because of industrial structure adjustment and upgrading.

### 3.4. Assessment of classification accuracies

Classification accuracies of seasonal impervious surface maps were assessed using a confusion matrix. Historical high resolution imagery acquired from Google Earth was adopted as the reference data. By referring to (McCoy, 2005), a stratified random sampling method was applied to select samples. This method assigns a specific number of samples to each class in proportion to the significance of the class within a classification. In this study, it was assumed that all classes were of equal significance to the classification. For each class, 1000 samples were randomly selected. For each class, these 1000 samples were divided into two parts: one was for training the classifier and the other was for an accuracy assessment. To ensure time consistency, the reference data were derived from stable areas in stacked clear-sky BCI images. With the aid of historical Google Earth imagery, pure pixels rather than mixed pixels in stable areas were selected. The seasonal overall accuracies and kappa coefficients for the classification maps between 2000 and 2016 are shown in Fig. 9.

In Fig. 9, the annual overall accuracy reached 88%. The curves of seasonal overall accuracies and kappa coefficients showed volatility. This was mainly due to missing data. For example, the overall accuracy on October 31, 2000 (78.43%) was higher than other seasons in 2000, because the cloud cover in the October 31 image was the lowest. The overall accuracy on February 13, 2004 was higher than September 16, 2004, because the image on September 16 was SLC-off data. Additionally, the overall accuracies in recent years were higher than in previous years. This is due to a higher temporal resolution of land cover temporal characteristics in recent years.

To verify the effectiveness of the proposed method in this study, the semi-supervised SVM algorithm, maximum likelihood classification, and neural net classification were directly applied to the spectral features to classify cloud-free Landsat images for each year. Since there were no available cloud-free images for 2013–2016, images with the least amount of cloud cover for these years were selected. The classification accuracies were assessed using the same evaluation method and reference data. The selected data are shown in Table 4. For the problem of missing data in images from 2013 to 2016, the same data preprocessing that was used for the proposed method was conducted. The overall accuracies and kappa coefficients of the comparison experiments are shown in Table 5. Table 5 shows that the proposed method, which applies the semi-supervised SVM on the temporal characteristics, had relatively higher classification accuracies than other traditional methods based on spectral information. Although the percentages of cloud cover in images from 2013 to 2016 were higher than other images, the semi-supervised SVM used for the temporal characteristics yielded reasonable classification accuracies. Therefore, the proposed method using temporal features achieved a higher level of classification accuracy than traditional methods using spectral features.

### 4. Discussion

Due to the rapid urbanization progress in China, the monitoring of impervious surface dynamics requires much higher temporal resolution than annual or decadal frequencies addressed by previous studies. This study focused on mapping impervious surface dynamics at a seasonal time scale based on temporal characteristics from time series Landsat data in WUA, China. The quantitative accuracy assessment showed that the proposed method performed well for estimating seasonal impervious surfaces. It is worthy to note that our findings on temporal
Fig. 7. Annual impervious surface maps in the study area from 2000 to 2016.
characteristics were consistent with the analysis of previous studies (Zhang and Weng, 2016; Zhang et al., 2017). The seasonal impervious surfaces also showed that overall, impervious surfaces do not increase in a progressive and gradual way, and they showed periods of rapid change.

However, there are several issues that require further study. One issue is the sub-pixel temporal characteristics. Pure pixels were difficult to yield using Landsat images with a spatial resolution 30 m. Because of the mixed pixel problem, impervious surfaces were often overestimated in inner urban areas and underestimated in rural areas (Lu and Weng, 2006). Meanwhile, low accuracies occurred in the suburban areas where the distribution of impervious surfaces was discrete. In addition, due to the complexity of impervious surface materials, there was a temporal variation seen in impervious surface pixels, whereas this study did not examine the temporal differences between different impervious surfaces. New methods for extracting sub-pixel impervious surfaces, while also considering temporal variations, need to be explored. Perhaps spectral and spatial information can be incorporated for identifying endmember candidates. Additionally, the nonlinearity of the mixture cannot be neglected. Nonlinear unmixing methods for temporal characteristics need to be developed. Another issue is the uncertainty in error propagation. Temporal characteristics were derived from seasonal time series BCI and NDISI, whereas cloud contamination was one of the biggest obstacles to generating seasonal time series datasets. Cloud-contaminated areas observed over a large time span showed low accuracies due to the errors from missing data filling (Zhang and Weng, 2016). Although cloud cover was removed using NSPI and SLC-off data was filled by GNSPI, the differences between the estimation values and

Table 4
Selected annual Landsat imagery for comparison experiment.

<table>
<thead>
<tr>
<th>Landsat Scene Identifier</th>
<th>Acquisition Date</th>
<th>Land Cloud Cover (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LT51230392000305BJC00</td>
<td>2000/10/31</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392001067BJC00</td>
<td>2001/3/8</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392002246BJC01</td>
<td>2002/9/3</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392003297BJC00</td>
<td>2003/10/24</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392004348BJC00</td>
<td>2004/12/13</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392005110BJC00</td>
<td>2005/4/20</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392006305BJC01</td>
<td>2006/11/1</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392007036BJC00</td>
<td>2007/2/5</td>
<td>0</td>
</tr>
<tr>
<td>LT71230392008351EDC00</td>
<td>2008/12/16</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392009249BJC00</td>
<td>2009/9/6</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392010316BJC00</td>
<td>2010/11/12</td>
<td>0</td>
</tr>
<tr>
<td>LT51230392011063BKT00</td>
<td>2011/3/4</td>
<td>0</td>
</tr>
<tr>
<td>LT71230392012042EDC00</td>
<td>2012/2/11</td>
<td>0</td>
</tr>
<tr>
<td>LC81230392013340LGN01</td>
<td>2013/12/6</td>
<td>0.03</td>
</tr>
<tr>
<td>LC81230392014279LGN01</td>
<td>2014/10/6</td>
<td>0.18</td>
</tr>
<tr>
<td>LC81230392015298LGN01</td>
<td>2015/10/25</td>
<td>0.01</td>
</tr>
<tr>
<td>LC81230392016066LGN01</td>
<td>2016/3/1</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Fig. 8. Quantification of impervious surfaces in the study area from 2000 to 2016.

Fig. 9. Seasonal overall accuracies and kappa coefficients for the classification maps between 2000 and 2016.
observation values contributed to the errors in classifications. The estimated values cannot completely replace the true values. Furthermore, except for the missing data problem, there are many other factors that influence the temporal profiles including the DOY distribution of Landsat imagery, phenology, temperature, moisture, etc. Thus, the effects of error propagation need to be addressed.

5. Conclusions

This study demonstrated the use of temporal characteristics to map impervious surfaces at the seasonal time scale. The contributions of this study include the following aspects. First, temporal characteristics of land covers derived from seasonal time series BCI and NDISI can be used to alleviate the issue of spectral confusion. Section 3.2 demonstrated that temporal characteristics increased the between-class distances and decreased the within-class distances. Additionally, seasonal time series BCI and NDISI increased the temporal resolution of impervious surface mapping. Seasonal impervious surface dynamics were helpful for building a relationship between urban expansion and urban ecological cycles on a fine time scale. Second, this study proposed a new method for classifying temporal characteristics. The semi-supervised SVM algorithm was applied to yield comparability in accuracies with other methods (PLSR and ANN). Remote Sens. Environ. 110, 59-78.

Table 5

<table>
<thead>
<tr>
<th>Year</th>
<th>Overall accuracy</th>
<th>Kappa coefficient</th>
<th>Year</th>
<th>Overall accuracy</th>
<th>Kappa coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>78.43%</td>
<td>0.74</td>
<td>2000</td>
<td>69.44%</td>
<td>0.64</td>
</tr>
<tr>
<td>2001</td>
<td>80.90%</td>
<td>0.76</td>
<td>2001</td>
<td>74.50%</td>
<td>0.69</td>
</tr>
<tr>
<td>2002</td>
<td>81.30%</td>
<td>0.76</td>
<td>2002</td>
<td>69.59%</td>
<td>0.64</td>
</tr>
<tr>
<td>2003</td>
<td>82.23%</td>
<td>0.77</td>
<td>2003</td>
<td>75.67%</td>
<td>0.70</td>
</tr>
<tr>
<td>2004</td>
<td>82.09%</td>
<td>0.77</td>
<td>2004</td>
<td>77.28%</td>
<td>0.73</td>
</tr>
<tr>
<td>2005</td>
<td>83.90%</td>
<td>0.79</td>
<td>2005</td>
<td>80.10%</td>
<td>0.74</td>
</tr>
<tr>
<td>2006</td>
<td>84.58%</td>
<td>0.80</td>
<td>2006</td>
<td>80.81%</td>
<td>0.76</td>
</tr>
<tr>
<td>2007</td>
<td>87.57%</td>
<td>0.82</td>
<td>2007</td>
<td>82.11%</td>
<td>0.77</td>
</tr>
<tr>
<td>2008</td>
<td>88.71%</td>
<td>0.83</td>
<td>2008</td>
<td>84.63%</td>
<td>0.80</td>
</tr>
<tr>
<td>2009</td>
<td>91.80%</td>
<td>0.86</td>
<td>2009</td>
<td>83.69%</td>
<td>0.79</td>
</tr>
<tr>
<td>2010</td>
<td>88.61%</td>
<td>0.83</td>
<td>2010</td>
<td>81.73%</td>
<td>0.76</td>
</tr>
<tr>
<td>2011</td>
<td>90.12%</td>
<td>0.84</td>
<td>2011</td>
<td>83.75%</td>
<td>0.79</td>
</tr>
<tr>
<td>2012</td>
<td>93.40%</td>
<td>0.90</td>
<td>2012</td>
<td>87.71%</td>
<td>0.82</td>
</tr>
<tr>
<td>2013</td>
<td>93.08%</td>
<td>0.90</td>
<td>2013</td>
<td>80.50%</td>
<td>0.75</td>
</tr>
<tr>
<td>2014</td>
<td>95.67%</td>
<td>0.93</td>
<td>2014</td>
<td>81.59%</td>
<td>0.76</td>
</tr>
<tr>
<td>2015</td>
<td>92.78%</td>
<td>0.89</td>
<td>2015</td>
<td>79.36%</td>
<td>0.74</td>
</tr>
<tr>
<td>2016</td>
<td>91.29%</td>
<td>0.85</td>
<td>2016</td>
<td>76.11%</td>
<td>0.72</td>
</tr>
</tbody>
</table>

5. Conclusions

This study demonstrated the use of temporal characteristics to map impervious surfaces at the seasonal time scale. The contributions of this study include the following aspects. First, temporal characteristics of land covers derived from seasonal time series BCI and NDISI can be used to alleviate the issue of spectral confusion. Section 3.2 demonstrated that temporal characteristics increased the between-class distances and decreased the within-class distances. Additionally, seasonal time series BCI and NDISI increased the temporal resolution of impervious surface mapping. Seasonal impervious surface dynamics were helpful for building a relationship between urban expansion and urban ecological cycles on a fine time scale. Second, this study proposed a new method for classifying temporal characteristics. The semi-supervised SVM algorithm was applied to yield comparability in accuracies with lower computational effort, and then, the improved classification results were obtained through application of seasonal scale temporal filtering. This work contributes to the usage of temporal characteristics for mapping impervious surfaces. Further work should focus on the effects of increasing amounts of impervious surfaces on urban environments. Moreover, the time scale of impervious surface dynamics largely depends on the rate of land cover changes. As various developments in city construction and land cover may change inter-annually, semi-annually, monthly or more frequently, the time scale can also be changed to annual, semi-annual, or monthly when applying the proposed method to other research regions.

Acknowledgment

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